CASE STUDIES OF POWER TRANSFORMER FAULT ANALYSIS

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***Abstract*: This paper deals with three types of power transformer failure analysis tests which can help in monitoring the transformer condition. The three methods are Conventional oil test, Furan derivatives test and Markov models criteria. Conventional oil testing procedure includes determination of various properties of the transformer oil sample and analyzing the fault. Furan derivative analysis includes determination of Furan derivatives present in the transformer oil sample and helps in deciding the transformer insulation condition. Hidden Markov model helps in finding out the fault probability of the power transformer. Here, we demonstrate the application of these three methods on three power transformers from three substations of Telangana and Andhra Pradesh, India, under three different conditions namely healthy, moderately deteriorated and extensively deteriorated conditions.**

***Keywords:* Transformer oil testing, Furan derivatives analysis, hidden Markov model, fault diagnosis, MATLAB.**

I. INTRODUCTION

Power transformers are important components of power systems. Their better performance implies high power system efficiency and enhanced power transfer capability. Different preventive, predictive and spontaneous repair techniques have been designed so far to eliminate or at least minimize the failures. In this paper, we try to illustrate three methods of testing the given power transformer's performance. The first one is oil sample test, wherein the transformer oil is tested for different properties like appearance, density, viscosity, acidity and thus the transformer condition can be analyzed. The second one is Furan derivatives test, wherein software program is used once the oil is subjected to Furan test. The software gives the corresponding reading and thus the performance can be known. The last one includes use of Hidden Markov Models, which require MATLAB coding. The outputs of these are failure probabilities of the given power transformer.

II. CONVENTIONAL OIL TESTING PROCESS

This is the most commonly undertaken method of testing power transformer efficiency. Oil samples are taken from the transformer and subjected to various tests and the results are analyzed before declaring the equipment fit or unfit.

The tests that are undertaken at the oil testing lab are briefly described below.

A. Colour And Visual:

This test checks the turbidity, cloudiness, suspended particles and colour. New oil is bright and clear without visual contaminants and pale yellow in colour. Hence, while testing the oil, the colour and brightness should be checked, indicating that turbidity, cloudiness and suspended particles are within limits.

B. Moisture Content :

The fresh oil sample should not have a moisture content of more than 40ppm. Therefore, when testing the transformer oil for moisture content, the test reading should not exceed 40ppm.

C. Dielectric Strength (Breakdown Voltage):

An oil sample is placed between two electrodes with a 2.5mm gap. A continuously increasing voltage is applied until the oil discharges at a certain voltage (kV). A sample of used oil should not breakdown before 40kV. If the oil sample breakdowns below 40kV, then the transformer oil needs to be replaced.

D. Neutralization (acid) number:

This test measures the neutralization number. When oil oxidizes in a transformer, acids and sledges are produced along with water. A severe increase in neutralization number can be detrimental to the insulation system. The neutralization number for used oil is 0.3 or less.

E. Power Factor :

This test measures the leakage current that passes through oil. Being a very sensitive indicator as far as deterioration is concerned, it has become one of the useful tests in the industry. The greater the power factor, the more polar the contamination is in the oil. However, it can be analyzed from the dissipation factor evaluation.

F. Dielectric dissipation factor (tan delta) test:

This test is also known as the loss tangent or dielectric dissipation factor measurement. Tan delta may be defined as the measurement of the cosine of the phase angle or the sine of the loss angle. It is basically the measurement of the leakage current through the oil, which in turn is a measure of the contamination or deterioration of the oil. The oil is non-polar and most other contaminants are polar, enabling a dipole action, which this test depends upon. A normal degree of refining will result in a low value for the power factor. The presence of contaminant such as engine oil can easily be detected with this parameter. An oil sample

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should not have tan delta value more than 1.0. Therefore, if the value is above 1.0, the oil has to be changed.

G. Specific Resistance:

At 90°C, the resistivity of transformer oil is supposed to be 0.1×10^{12}ohm-cm. The transformer oil test sample at 90°C will have a specific resistance of less than 0.1×10^{12}ohm-cm if the oil is old and of poor quality, requiring replacement.

H. Density:

The density of the sample oil is also to be taken into account for the analysis. The preferred value of density is less than $0.89 g/cm^3$. Hence, when the test reading for oil density is more than $0.89 g/cm^3$, it indicates that the oil has to be changed.

I. Flash Point:

The flash point is a key factor in the oil tests. It should not be reached before 140˚C for the oil to be of good quality. Hence, when oil samples are tested for flash point, they should attain the flash point after the minimum limit of 140˚C to declare that the oil is good with respect to flash point characteristics.

J. Flash Point:

The oil's viscosity is to be maintained below $27 m^2/s$ at 27˚C. Hence, an oil sample of viscosity greater than $27 m^2/s$ needs replacement.

III. Furan Derivatives Test

This is another method undertaken to prevent power transformer failures. The amount of Furan derivatives denotes the degree of degradation of the cellulose paper used in the insulation. However, other procedures for determining the healthiness of the transformer based on the cellulose paper used in the transformer insulation are very difficult, time consuming and tedious. Here comes the need of Furan derivatives test wherein the amount of furans in the oil can be computed using High Performance Liquid Chromatography (HPLC) apparatus and thus the aging of paper insulation can be analyzed. Furan(C_4H_4O) is obtained from the compound Furfural, which is also called Furan-2-carboxaldehyde, Fural, Furfuraldehyde, 2-Furaldehyde, Pyromucic aldehyde, with chemical formula OC_4H_3CHO. The furans are reported in ppm (parts per million).

The results can be used to compute average degree of polymerization (DP) thereby estimate the percentage of residual life of the solid insulation. As the paper ages, the polymer chains breakdown slowly, and the mechanical strength of the paper reduces. As the degree of polymerization (DP) decreases by the age, till it reaches 200 units, the insulation paper gets so weak that any further stress will disrupt the paper and lead to failure. Electrical insulating oil analysis can play a vital role in preventing unscheduled outages in electrical transmission and distribution equipment by determining the condition of the equipment itself and other factors like paper insulation.

The reference standard for the Furan derivative test **[4]** is given in Table-1.

Table-1: Reference Standards for Furan Derivatives Test

Furaldehyde content (ppm)	DP value	Significance
<0.1	700-1200	Healthy
0.1-1	450-700	Moderate deterioration
1-10	250-450	Extensive deterioration
>10	<250	End of life

IV. Hidden Markov Model

Markov Model is the one wherein, the state is directly visible to the user and the state transition probabilities are the only parameters. However, a 'Hidden Markov Model' has state not directly visible i.e., the state is "hidden" and output, which is dependent on the state, is visible. The state sequence through which the model passes is 'hidden' and not the parameters of the model. In fact, even when the parameters are exactly known, the model is still 'hidden'. The hidden Markov model can be said to be a generalization of a mixture model where hidden variables that monitor the mixture components to be selected for the observation, are co-related through a Markov process rather than independent of each other [1].

A) Architecture Of A Hidden Markov Model

General architecture of an HMM is shown in the **Figure1**. The random variable 'x(t)' is the hidden state at time 't' i.e., 'x(t)' $\in \{x_1,x_2,x_3\}$. The random variable 'y(t)' is the observation at time 't' where 'y(t)' $\in \{y_1,y_2,y_3,y_4\}$. The arrows denote conditional dependencies. The conditional probability distribution of the hidden variable 'x(t)' at time 't' depends only on the value of the hidden variable x(t−1) and the values at time (t−2) and before have no effect. This is called the 'Markov property'. Similarly, the value of the observed variable 'y(t)' only depends on the value of the hidden variable 'x(t)' (both at time 't').

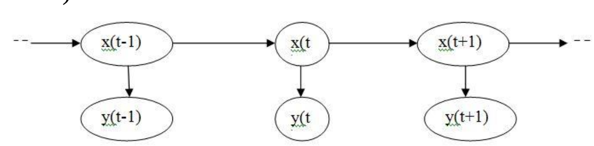

Figure1: General architecture of HMM

The hidden state space is assumed to consist of one of 'N' possible values. This means that for each of the 'N' possible states, there is a transition probability from this state to each of the 'N' possible states of the hidden variable at time (t+1), for a total of 'N^2' transition probabilities.

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In addition, for each of the 'N' possible states, there is a set of emission probabilities controlling the distribution of the observed variable at a particular time given the state of the hidden variable at that time. The size of this set depends on the nature of the observed variable. For example, if the observed variable is discrete with 'M' possible values, there will be '(M−1)' separate parameters, for a total of 'N (M−1)' emission parameters over all hidden states. On the other hand, if the observed variable is an M-dimensional vector distributed according to an arbitrary multi-variable Gaussian distribution, there will be 'M' parameters controlling the means and 'M(M+1)/2' parameters controlling the co-variance matrix, for a total of '$N(M+M(M+1)/2)=NM(M+3)/2=O(NM^2)$' emission parameters.

(In such a case, unless the value of 'M' is small, it may be more practical to restrict the nature of the co-variances between individual elements of the observation vector, e.g. by assuming that the elements are independent of each other or independent of all but a fixed number of adjacent elements).

B) Procedure For Using HMM Algorithm

Learning:

This procedure is used to find the best set of state transition and output probabilities. It is generally used to obtain the HMM parameters from the known set of output sequences. There is no particular algorithm for exactly solving this problem. However, a local maximum likelihood can be arrived at using Baum-Welch algorithm or Baldi-Chauvin algorithm.

Filtering:

This is to compute the distribution over hidden states at the end of the sequence, using the model's parameters and a sequence of observations i.e., to compute $P[x(t) \mid y(1),y(2),...,y(t)]$. This problem can be taken up efficiently using Forward algorithm [2].

A. Computing Probability Of An Observed Sequence:

Here, the task is to compute the probability of a particular output sequence from the given parameters of the model. This requires summation over all possible state sequences. The probability of observing a sequence $Y=y(0),y(1),...,y(L-1)$ of length 'L' is given by $P(y) = \Sigma P(y/x) P(x)$ where the sum runs over all possible hidden-node sequences $X=x(0),x(1),...,x(L-1)$. Applying the principle of dynamic programming, this problem too can be handled using Forward algorithm.

Smoothing:

This is to calculate the probability distribution over hidden states for a point in time in the past. The parameters of the model and a particular output sequence upto time 't' are known. We need to compute probability distribution for some $k<t$. The Forward-Backward algorithm is an efficient method for calculating the smoothed values for all hidden state variables.

Statistical Significance:

When an HMM is used to evaluate the relevance of a hypothesis for a particular output sequence, the statistical significance indicates the false positive rate associated with accepting the hypothesis for the output sequence.

C) Applications Of Hidden Markov Models

HMMs can be applied in many fields where the goal is to recover a data sequence that is not immediately observable (but other data that depends on the sequence is observable). Common applications include Cryptanalysis, Speech recognition, Part-of-speech tagging, Machine translation, Partial discharge, Gene prediction, Alignment of bio-sequences, Activity recognition.

D) Application Into The Fault Diagnosis Field

The Fault Classification:

Although the method based on the dissolved gases analysis has some characteristics which indicate that identification method is simple and fault classification result is explicitly specific, yet the classification and boundary of this method is over absolute in practice. There still exist some mistaken phenomena which include: (1) Many compound fault problems aren't still solved carefully in actual such as electric discharge merge overheat; (2) There exit some overlap distribute phenomena in the ratio boundary adjacent. Therefore, there are still many misjudges, lacking judges or non-judging cases during the actual fault diagnosis. The occurrence probability of these cases is relatively small and will be not considered when large quantity power transformers are counted and analyzed. But, these cases shouldn't be ignored and the DGA method should be improved for each power transformer. Each ratio in the new IEC three ratios method has different space interval. Based on the data statistics for large quantity power transformers with fault and referenced to some relative classification methods, the fault pattern for power transformer is classified as seven types. They include: normal, overheat under moderate or low temperature (not more than 700˚C), overheat under high temperature (more than 700˚C), discharge under low-energy, discharge under high-energy, discharge under low-energy merge overheat, discharge under high-energy merge overheat.

Characteristic Variables Determination:

The purpose that some useful information obtained from the DGA data is to proceed for the pattern identification. The gas ratio selection and the characteristic dimensional will determine the fault classification correctness to some degree. There are several useful characteristic gases to judge oil filled transformer inner faults: hydrogen, methane, ethane, ethane, acetylene, ethylene, carbon monoxide and carbon dioxide. However, because of the easy presence of carbon dioxide in the air and insensitiveness to the faults, carbon dioxide shouldn't be considered as a fault characteristic gas. When some latent faults on power transformer occur, the carbon monoxide gas density may be much more than that of other

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characteristic gases. It will have an effect on the output probability computation in HMM model building and pattern classification for the other characteristic gases produced. In order to simplify problems and combine the actual condition for HMM model building and fault classification, there are five gases selected. They are hydrogen, methane, ethane, ethylene and acetylene. Carbon monoxide is considered as one of the characteristic gases to measure the power transformer running state. Now, the characteristic gas vector quantity composed of Dissolved Gas Analysis(DGA) data can be shown as $X = [H_2, CH_4, C_2H_6, C_2H_4, C_2H_2]$.

HMM Training And Fault Diagnosis Model Library Establishing:

HMM is trained as a representative of the power transformer normal working condition to the power transformer fault diagnosis. For all possible occurrence fault patterns, the HMMs are trained and a fault diagnosis model library is prepared. In order to judge a characteristic gas attribute to which types of fault, the signal must be preconditioned, and then compute each model's output probability in fault model library, compare all probabilities, take out the maximal output probability model and make the final fault decision. The output probability computation can be realized by the forward-backward algorithm or Viterbi algorithm. There are four hidden states to simulate the power transformer running pattern during HMM model building and it is assumed that the HMM model is a left-right type and the initial probability distribution vector quantity is $\Pi=[1,0,0,0]$. The hidden states can be denoted by the circle graduation with digitals shown in the **Figure2**. The arrows show the inter-dependency of variables and the symbols up the arrow show the state transition probabilities. As they reside in the state, each state can observe some vector quantity sequence, and O1,O2,...,OT, are all expressed as variance observed value vector quantities.

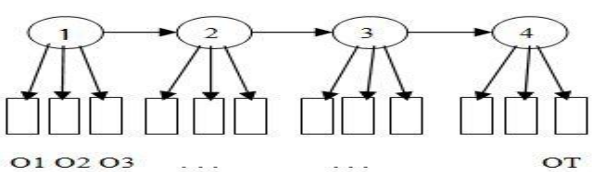

Figure-2: HMM training and fault diagnosis model library establishing

HMM Training Process:

Once the HMM initial model is established, the training of HMM can be obtained by the iterative computation using the recurrence-thought Baum-Welch algorithm. The logarithmic value of maximum likelihood estimated value will be increasing till the convergence error and end since the iterations increase in HMM. Training of HMM has rapidly leaning performance and would have reached the convergence error in several steps domain in general. The important outputs after model training are state transition probability matrix and observable value probability matrix. The five fault patterns that include normal, overheat under moderate or low temperature, overheat under high temperature, discharge under low-energy, discharge under high-energy are modeled respectively by HMM. Each model training iterative curve shows that HMM has strong learning ability.

HMM Fault Diagnosis:

This is used for classification. Different fault characteristic patterns should build HMM, and the characteristic gas observable value can be used to quantify the sequence at fault classification. The probability '$P(O|\lambda)$' is calculated and reasoned by the forward-backward algorithm or Viterbi algorithm, then the probability output result is compared and the decision is made by the maximal output. For example, if 'λ_i' output probability is at the most, the fault pattern 'ω_i' will be judged. The quantification sequence for the characteristic gases observable vector quantity given by $X = [H_2, CH_4, C_2H_6, C_2H_4, C_2H_2, CO, CO_2]$ will be used as the input vector quantity, and the fault is classified by the built-in HMM. There are two types of outputs for HMM classification. The first one is HMM export logarithmic likelihood probability computation result. Another is the fault possibility corresponding to each of fault modes.

V. Fault Diagnosis System Design

The design concept for the fault diagnosis system based on HMM for a power transformer is: first the HMM will be trained by using various faults measuring data and the HMM fault model library is established. Then, the algorithm program that is used to classify fault and to compute each HMM probability output is designed as COM module, and is ready to be called by the main program. Now, the collecting characteristic gas data will be sent to display and monitor on real time monitoring window after preconditioning and at the same time the data is stored in data base. If the data exceeds the threshold value set beforehand, the monitoring window will give 'out-of-tolerance' alarm, and store the out-of-tolerance data. The doubtful data is then diagnosed after the out-of tolerance data is analyzed and judged. The possible fault type and the fault occurrence probability will also be obtained. Finally, the power transformer is correspondingly treated as per the HMM diagnosis, combining other fault diagnosis methods with off-line testing conclusions. The system software is based on the main program and includes each functional module, which simplify the software design structure. The system architecture includes four parts: data collecting and handling module, data display in real-time and monitoring module, data store and inquiring module, HMM model library and intelligent fault diagnosis module. The overall frame for the diagnosis system is as shown in the **figure-3** below.

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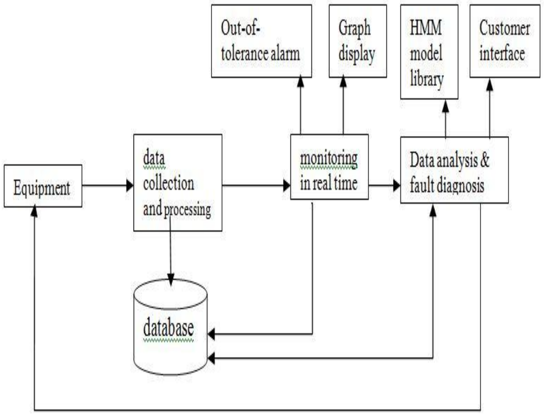

Figure3: The overall frame for the diagnosis system

The main steps in the frame for the HMM process include:

Fetch data from the data collecting card and proceed to dispose.

Monitor the characteristic gas data in real–time and display graph, give alarm when the data is out-of tolerance.

Finish the interactive operation between the application program and the data base; realize the data store and transmission.

HMM fault diagnosis module can diagnose the equipment fault when it occurs and can combine with the other fault diagnosis methods to proceed to synthesis judge.

The HMM method is thus used to get the fault diagnosis i.e., fault probability of the transformer with the help of MATLAB coding on a computer.

VI. Flowchart For The Hidden Markov Models Program [6]

A flowchart for the fault diagnosis using HMM is shown in the **Figure4** below.

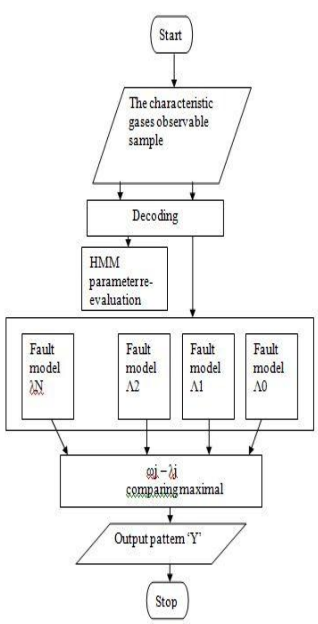

Figure4: Flowchart for HMM program

Description of the flowchart:

The characteristic gases from the power transformer oil sample are taken. Decoding is done for them so as to be understandable to the system.

Fault models from the fault model library are compared with the input gas concentrations.

The fault model which is most similar i.e., having the maximal output with respect to the input, is considered and is given as output.

VII. Tests On An Oil Sample

Oil samples were collected from power transformers located at three different substations namely 132kV Vijayawada substation (Andhra Pradesh), 220kV Chandrayanagutta substation (Telangana) and 132kV Port substation (Andhra Pradesh) [2]. MATLAB program was designed and run for getting the failure probability percentages for Hidden Markov Models method.

The test results for the power transformers under different conditions are shown in the Tables- 2 to 10.

Power Transformer Oil Sample Test Results under Healthy Condition:

The test results for the power transformer under moderately deteriorated condition are shown in the Tables- 2 to 4.

Table-2: Conventional Oil Test Results

Sl. No.	Oil parameter	Reference standard	Limit	Result	Remarks
1.	Appearance	Clearness	Clear & bright	Clear & bright	Satisfactory
2.	Water content (ppm)	170kV & above	20 max	NA	NA
		72.5kV-170kV	40 max	4.4	Satisfactory
		Below 72.5kV	No free water	NA	NA
3.	Breakdown voltage (kV)	170kV & above	50 min	NA	NA
		72.5kV-170kV	40 min	60.1	Satisfactory
		less than 72.5kV	30 min	NA	NA
4.	Acidity (mg of KOH/g)	all voltages	0. 3 max	0.2	Satisfactory
5.	Dielectric dissipation factor (Tan delta)	170kV & above	0.2 max	NA	NA
		below 170kV	1.0 max	0.00385	Satisfactory
6.	Resistivity (Ω-cm)	all voltages	0.1E12 min	32.18E12	Satisfactory
7.	Density (g/cm^3)	all voltages	0.89 max	0.75	Satisfactory
8.	Flash point (˚C)	all voltages	140 min	152	Satisfactory
9.	Viscosity (m^2/s)	all voltages	27 max	22	Satisfactory

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Remarks: Results are within limits i.e., the transformer is “healthy”.

ND – Not Determined. NA – Not Applicable.

The test results of Furan derivative analysis of the above transformer is shown in the Table-3 given below.

Table-3: Furan Derivative Test Results

2- FURALDEHYDE (mg/kg)	0.0007

Remarks: The transformer is “healthy”.

For the hidden Markov model (HMM) analysis results, **t**he input characteristic gases observable vector quantity is *X*=[67,14,1.3,3.2,0], HMM classification output result is showed in Table-4, where the identification results are for discharge under high-energy, and the fault occurrence probability is **52.32 %**.

Table-4: HMM Classification output Results

Output	Normal	Overheat under moderate or low temperature	Overheat under high temperature	Discharge under low energy	Discharge under high energy
Logarithmic likelihood probability	-Infinity	-6.9386e-1	3.4370e+1	1.572e+1	2.515e+0
Fault possibility (%)	8.03e+0	6.3113e+0	**5.2323 e+1**	5.946 e+1	1.046 e+2

Power Transformer Oil Sample Test Results Under Moderately Deteriorated Condition:

The test results for the power transformer under moderately deteriorated condition are shown in the Tables – 5 to 7.

Table-5: Conventional Oil Test Results

Sl. No.	Oil parameter	Reference standard	Limit	Result	Remarks
1.	Appearance	Clearness	Clear & bright	Clear & bright	Satisfactory
2.	Water content (ppm)	170kV & above	20 max	NA	NA
		72.5kV-170kV	40 max	11.7	Satisfactory
		Below 72.5kV	No free water	NA	NA
3.	Breakdown voltage (kV)	170kV & above	50 min	NA	NA
		72.5kV-170kV	40 min	45	**Marginally satisfactory**
		less than 72.5kV	30 min	NA	NA
4.	Acidity (mg of KOH/g)	all voltages	0. 3 max	0.2	Satisfactory
5.	Dielectric dissipation factor (Tan delta)	170kV & above	0.2 max	NA	NA
		below 170kV	1.0 max	0.00074	Satisfactory
6.	Resistivity (Ω-cm)	all voltages	0.1E12 min	260E12	Satisfactory
7.	Density (g/cm^3)	all voltages	0.89 max	0.75	Satisfactory
8.	Flash point (˚C)	all voltages	140 min	153	Satisfactory
9.	Viscosity (m^2/s)	all voltages	27 max	22	Satisfactory

Remarks: Results are not within limits i.e., the transformer is “moderately deteriorated”.

ND – Not Determined. NA – Not Applicable.

The test results of Furan derivative analysis of the above transformer is shown in the Table- 6.

Table-6: Furan Derivatives Test Results

2-FURALDEHYDE (mg/kg)	0.21

Remarks: The transformer is “moderately deteriorated”.

For the hidden Markov mode analysis results, **t**he input characteristic gases observable vector quantity is *X*=[188.32,56.11,214.86,21.63,54.54]. HMM classification output result is showed in Table-7, where the identification results are for discharge under high-energy, and the fault occurrence probability is **62.059 %**.

Table-7: HMM Classification output Results

Output	Normal	Overheat under moderate or low temperature	Overheat under high temperature	Discharge under low energy	Discharge under high energy
Logarithmic likelihood probability	-Infinity	1.1659e+2	5.9730e+1	3.457e+1	6.632e+2
Fault possibility (%)	8.6e+1	5.1340e+1	**6.2059e+1**	2.525e+1	3.602e+2

Power transformer oil sample test results under extensively deteriorated condition:

The test results for the power transformer under extensively deteriorated condition are shown in the Tables- 8 to 10.

Table-8: Conventional Oil Test Results

Sl. No.	Oil parameter	Reference standard	Limit	Result	Remarks
1.	Appearance	Clearness	Clear & bright	Clear & bright	Satisfactory
2.	Water content	170kV & above	20 max	NA	NA
		72.5kV-170kV	40 max	29.8	Satisfactory

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	(ppm)	Below 72.5kV	No free water	NA	NA
3.	Breakdown voltage (kV)	170kV & above	50 min	NA	NA
		72.5kV-170kV	40 min	39.2	**Unsatisfactory**
		less than 72.5kV	30 min	NA	NA
4.	Acidity (mg of KOH/g)	all voltages	0. 3 max	ND	NA
5.	Dielectric dissipation factor (Tan delta)	170kV & above	0.2 max	NA	NA
		below 170kV	1.0 max	0.00733	Satisfactory
6.	Resistivity (Ω-cm)	all voltages	0.1E12 min	2.91E12	Satisfactory
7.	Density (g/cm^3)	all voltages	0.89 max	ND	NA
8.	Flash point (˚C)	all voltages	140 min	151	Satisfactory
9.	Viscosity (m^2/s)	all voltages	27 max	ND	NA

Remarks: Thermal fault more than 700˚C is suspected in the transformer.

ND – Not Determined. NA – Not Applicable.

The test results of Furan derivative analysis of the above transformer is shown in the Table-9.

Table-9: Furan Derivatives Test Results

2- FURALDEHYDE (mg/kg)	2.3

Remarks: The transformer is "extensively deteriorated".

For the hidden Markov mode analysis results, **t**he input characteristic gases observable vector quantity is *X*=[235.07,49.07,117.4,15.7,62.9]. HMM classification output result is showed in Table-10, where the identification results are for discharge under high-energy, and the fault occurrence probability is **72.66 %.**

Table-10: HMM Classification output Results

Output	Normal	Overheat under moderate or low temperature	Overheat under high temperature	Discharge under low energy	Discharge under high energy
Logarithmic likelihood probability	-Infinity	5.6578e+0	2.1030e+1	1.1314e+1	5.7951e+1
Fault possibility (%)	4.8e+1	2.0345e+1	**7. 266e+1**	1.5059e+1	1.6505e+2

VIII. CONCLUSIONS

In this paper, we have explained three different methods of determining the power transformer failure condition and failure probability. The Conventional Oil testing analysis, which is widely used, helps in thorough checking of the oil samples for various properties like colour, density, viscosity, resistivity etc., from which the condition of the transformer can be monitored. `Furan derivatives analysis helps in assessing the condition of insulation of the transformer windings. If the concentration of the Furaldehyde is more than 0.1 ppm, then the paper insulation has to be replaced. The Hidden Markov Model analysis helps to evaluate the fault probability of the transformer. A computer program was developed for Hidden Markov Model method and successfully implemented.

In this paper, power transformer oil samples were taken out from three different substations and tested for fault analysis.. All the above mentioned tests were conducted on these oil samples. The Conventional oil tests, Furan derivatives test and HMM analysis have been presented.

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